

UCI-ITS-TS-WP-04-4

**Exploring the Relationship between
Freeway Speed Variance, Lane Changing
and Vehicle Heterogeneity**

UCI-ITS-TS-WP-04-4

Seri Park
Stephen G. Ritchie

Department of Civil and Environmental Engineering and
Institute of Transportation Studies
University of California, Irvine
serio@uci.edu, sritchie@uci.edu

January 2004

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
<http://www.its.uci.edu>

Exploring the Relationship Between Freeway Speed Variance, Lane Changing, and Vehicle Heterogeneity

Seri Park *

Department of Civil and Environmental Engineering and
Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697 – 3600, U.S.A
Tel) +1-949-824-5623
Fax) +1-949-824-8385
serio@uci.edu

Stephen G. Ritchie

Department of Civil and Environmental Engineering and
Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697 – 3600, U.S.A
Tel) +1-949-824-4214
Fax) +1-949-824-8385
sritchie@uci.edu

Word Count : $3,459 + 14 * 250 = 6959$

*** Corresponding Author**

**Paper Submitted to the 83rd Annual Meeting of the Transportation Research Board,
January 11-15, 2004, Washington D.C.**

Exploring the Relationship Between Freeway Speed Variance, Lane Changing and Vehicle Heterogeneity

ABSTRACT

Accidents can be described as the breakdown of the complex interaction among road geometry, traffic conditions, driver behavior, and environmental characteristics. Out of these factors, speed variance is known to be highly correlated with the potential or actual accident rate. The proposed study presents a statistical analysis between driver's lane changing behavior and speed variance as well as that of vehicle heterogeneity and speed variance. Detailed individual level vehicle information is obtained with the use of state-of-the-art technology in traffic monitoring. Investigation and identification of factors influencing speed variance will help to establish countermeasures that will minimize speed variability, and thus improve traffic safety.

Key Words : Speed variance, vehicle signature, vehicle classification, driver's lane changing behavior, vehicle heterogeneity, vehicle trajectory

INTRODUCTION

Accidents may be viewed to result from complex function of multiple variables including road geometry, speed limit, driver's behavior, traffic conditions, and environmental factors. Identification of the proper relationship between these variables and traffic safety can help to reduce the possibility of an accident as well as to make the traffic more stable. Many studies have been performed in order to determine the factors affecting accident rate, and traffic safety. Speed variance has been found to be one of the major, if not the major, factor related to the road accident frequency. Previous studies show that road geometry, difference between posted speed limit and design speed are major factors affecting speed variance variability. On the other hand, the assumption of high correlation between speed variance and driver's lane changing behavior is quite reasonable but needs further statistical analysis and quantification. However, the effect of microscopic level traffic information (such as driver's lane changing) on speed variance, is not easy to capture from most widely used traffic data collection devices, such as conventional inductive loop detector (ILD). Because of this limitation, little investigation has been carried on driver's lane changing behavior impact on speed variance.

With new advanced technology in the detector field, it is now possible to get valuable traffic data not available in the past. Such information includes individual vehicle trajectories through which driver's lane changing pattern can be identified. Also, real time, accurate vehicle classification will determine vehicle heterogeneity. Therefore, using this traffic data, this study examines and conducts a statistical analysis of speed variance and two main traffic data : lane changing and vehicle heterogeneity. One of the innovative aspects of the study is to use section speed variance, which is postulated to reflect traffic change more accurately, instead of point speed variance. The overall concept of this study is expressed in Figure 1.

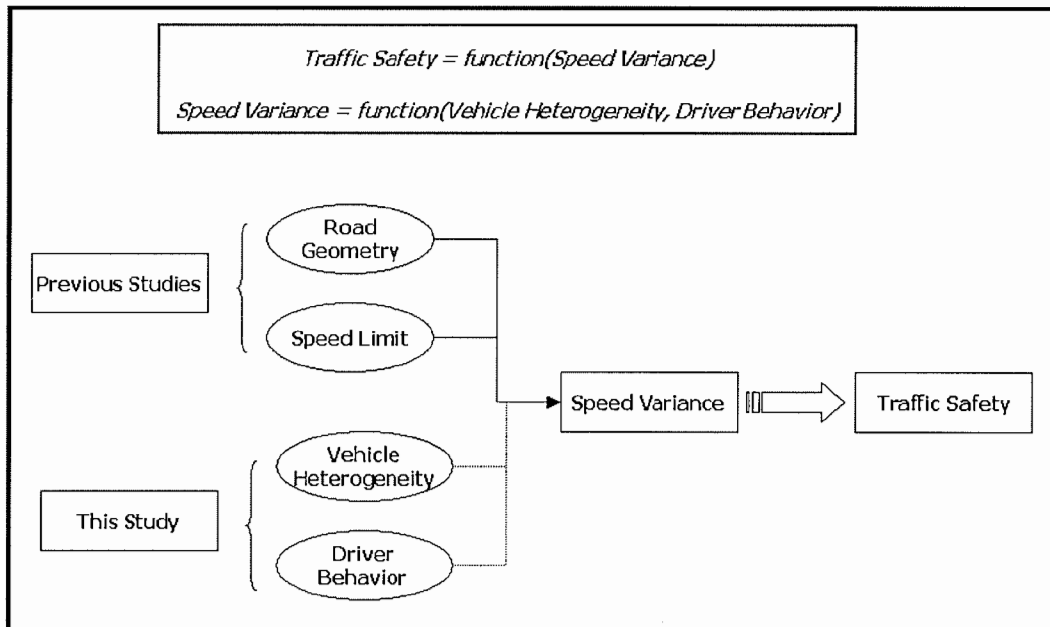


Figure 1. Proposed Study Concept

In summary, the objectives of this study are

- Statistical analysis and quantification of the relationship between speed variance and driver's lane changing behavior
- Statistical analysis and quantification of relationship between speed variance and vehicle heterogeneity

It should be noted that this study is more concerned with the trends in the data curve of speed variance and other factors, not with the statistical significance of the regression model building.

This paper consists of 5 sections including this introduction. Previous studies on safety and speed variance analysis are presented in section 2. Review on factors affecting on speed variance, and advanced loop detector technology are described in this section. Section 3 focuses on the development of the study framework. Illustrations on the study site, dataset, and result analysis are followed in section 4. The final section is dedicated to the contribution and future application of the proposed methodology.

BACKGROUND

Studies on finding the relationship of speed variance and traffic stability or safety are first mentioned. A review on the factors affecting speed variability will be followed. Finally, the description on the new advanced sensor card is presented.

Literature Review

Speed variance vs safety/stability

Many studies have been investigated to define the relationship between speed variance and accident rate or traffic stability. Findings from the research conducted by the Ministry of Transport and Communication, in Canada(1) and by Pisarski(2) suggested significant correlation between speed variance and accident rate. The studies from Solomon(3), Cirillo(4), and Munden(5) show that accident rates were lowest for drivers whose observed speeds were closet to the mean speed. A similar pattern was also found by Cerrelli et al(6), U-shaped curve between speed and accident rate, having the lowest accident rate around the average speed value where speed variance is supposed to be minimum. Garber et al(7) also pointed out that the speed variance increases with the difference between design speed and limit speed increases, consequently leading to higher accident rate for both highway and arterial cases. They also demonstrated driver's tendency to drive at increasing speeds as road geometry characteristics improve, regardless of the posted speed limit and accident rate increasing pattern. Accident rates do not necessarily increase with an increase in average speed but do increase with an increase in speed variance. Feng(8) recommends speed variance reduction to encourage stable flow.

Another approach is to examine the best indicator that could represent traffic instability or potential crash/accident rate. Studies from Hughes et al(9) and Corby(10) describe that changes in speed provide the best indicator of flow changes. Similar findings, that speed variance is the most significant indicator for potential accident/crash frequency, were also derived from Oh et al(11) and Lee et al (12).

Factors affecting speed variance

Elmberg's (13) study shows that the conflict between road geometry with corresponding speed limit tends to create high speed-variance. In other words, a low speed limit with good geometry will result in a wide range of speeds on the highway, which in turn will lead to an increase in accident rate. Garber et al(7, 14) proved that the difference between design speed and posted speed has significant effect on speed variance and recommended some guidelines for posting speed limits for different design speeds. Collins(15) study suggests that in general there is low correlation between geometric features and speed variance, but large differences in speed variance existed for the different design speed and posted speed. Recent study from Fidzpatrick et al(16) also concluded the posted speed to be the most significant factor for speed change on suburban road.

As we can see from above literature review, many studies have been focused on the speed variance related to accident rate but little investigation was done to identify the factors affecting speed variance. The proposed study aims to determine the functional curve between speed variance and traffic variables. With the use of individual vehicle level information, obtained from advanced loop detector technology, this approach can also be tested and validated on the field.

Vehicle Signature

Inductive loop detector (ILD) is the most widely applied device for the traffic data collection over the world. Conventional ILDs are operated in binary mode according to vehicle presence. In other words, loop inductance change output is "1" when the vehicle is detected and "0" otherwise. Recent technology advances in detector cards produce more detailed inductance change with the fast scanning interval. Therefore, each vehicle generates unique inductance change according to its shape, speed, and driver's behavior. Vehicle signature refers to this inductance change of individual vehicle. Some signature samples are illustrated in Figure 2. It is obvious that vehicle signature is function of vehicle type and using this concept, vehicle classification is performed in the following section.

In this study vehicle signature feature is categorized into two types : vehicle specific feature vector and traffic specific feature vector. Vehicle specific feature vector represents the features that are unique according to vehicle itself, therefore, invariant over time or location. Vehicle length is a good example for this category. Traffic specific feature vector indicates the features that could describe either traffic condition or road geometry. Speed and lane information falls into this category.

By processing the raw vehicle signature, five vehicle specific features are derived. Figure 3 and Table 1 explain these five elements : Vehicle electronic length, maximum magnitude, shape parameter (SP), degree of symmetry (DOS), and number of high magnitude (NHM). SP and DOS are similar in that they both denote the signature symmetry degree. But DOS captures the upper part signature symmetry whereas SP is more dedicated to represent the overall signature symmetry.

Many informative and valuable studies were completed (17 - 22) using vehicle signatures.

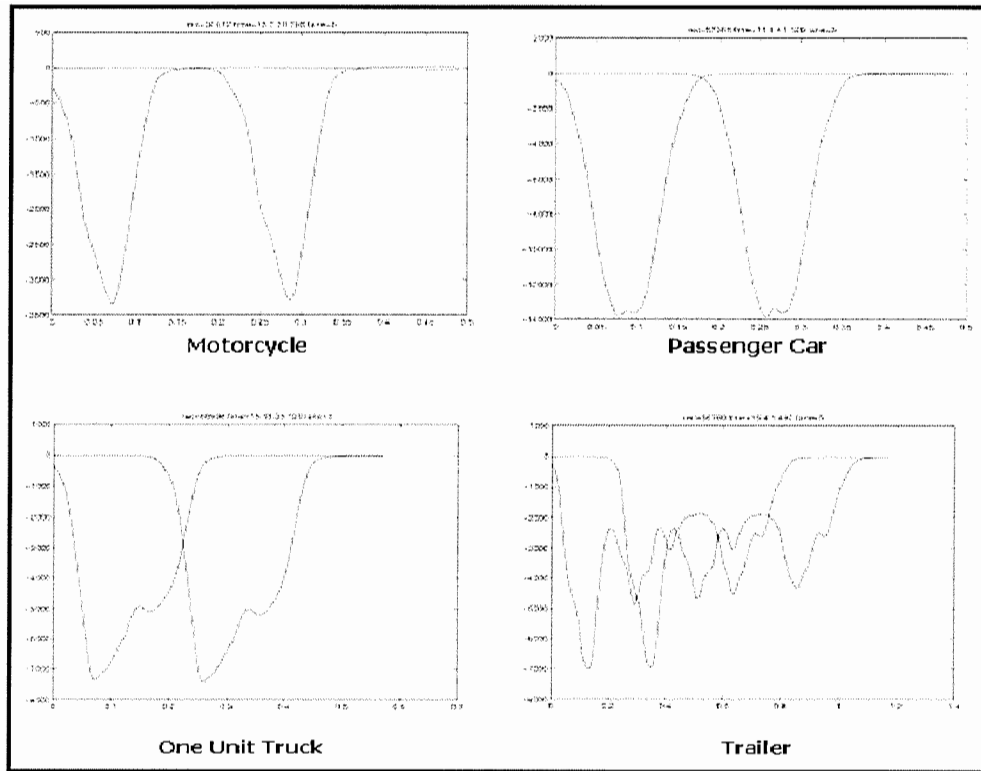


Figure 2. Example Signature

Table 1. Signature Feature

Feature Vector	Feature Description
Maximum Magnitude	Maximum absolute magnitude value (a)
Shape Parameter (SP)	Degree of Symmetry ((b)/(b+c))
Electronic Vehicle Length	(d)
Degree of Symmetry (DOS)	Degree of Symmetry e : median Sum of the distance from median g, to each point that is above "0.5" y value
Number of High Magnitude (NHM)	Sample number above "0.5" y value after x,y normalization

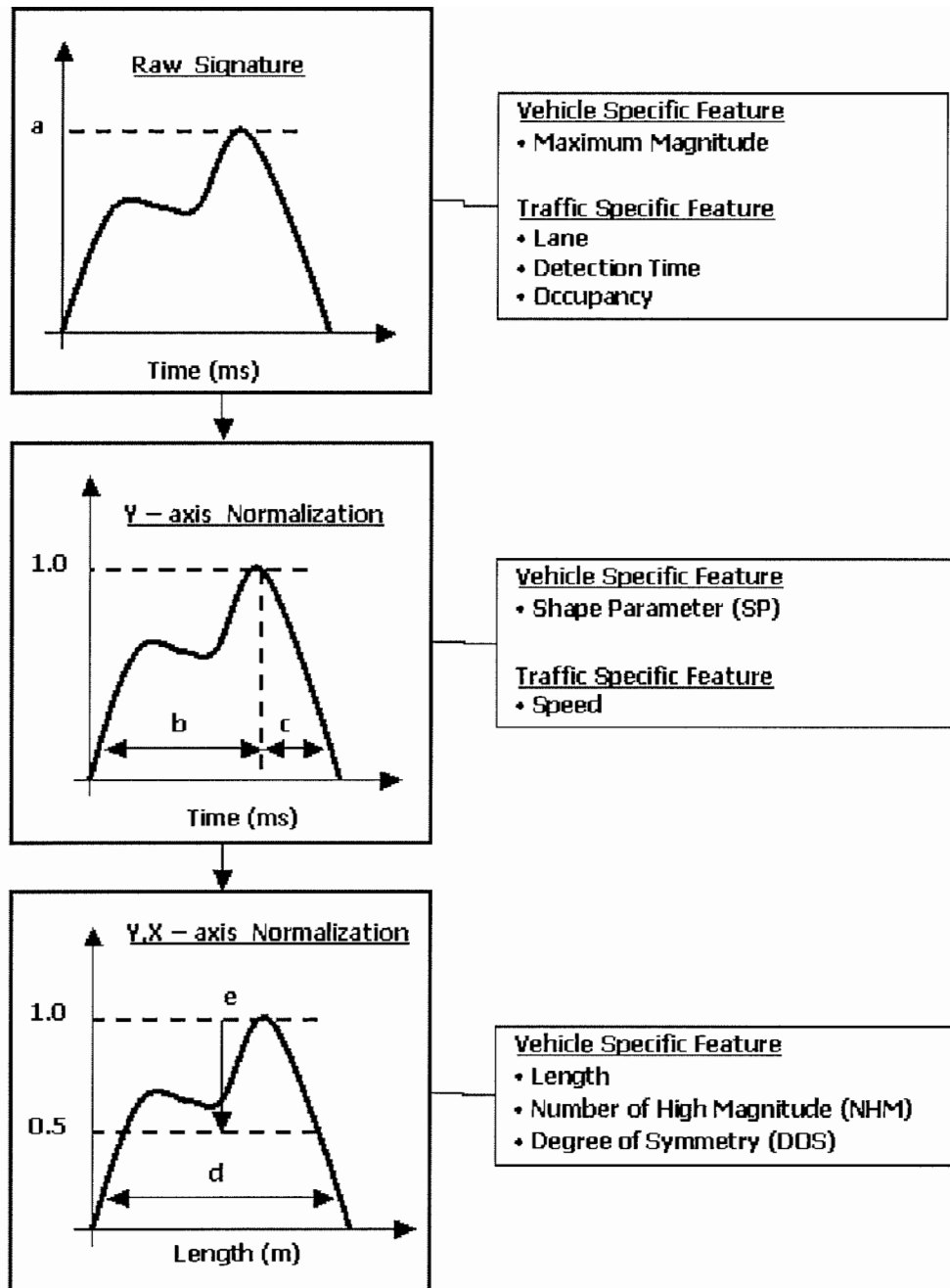


Figure 3. Signature Feature

METHODOLOGY

The main objective of this paper is to demonstrate and quantify the relationship of speed variance and driver's lane changing behavior as well as that of speed variance and vehicle heterogeneity. As explained from the previous Figure 1, speed variance is one of the main factors influencing traffic safety. Therefore, it is also important to define elements affecting speed variance to investigate traffic safety. In this section, using vehicle signatures, the procedures of vehicle clustering, and individual vehicle trajectory derivation are mentioned. Hypothesis test is also performed for observed and derived speed variance distribution.

Figure 4 shows the overall framework of this paper.

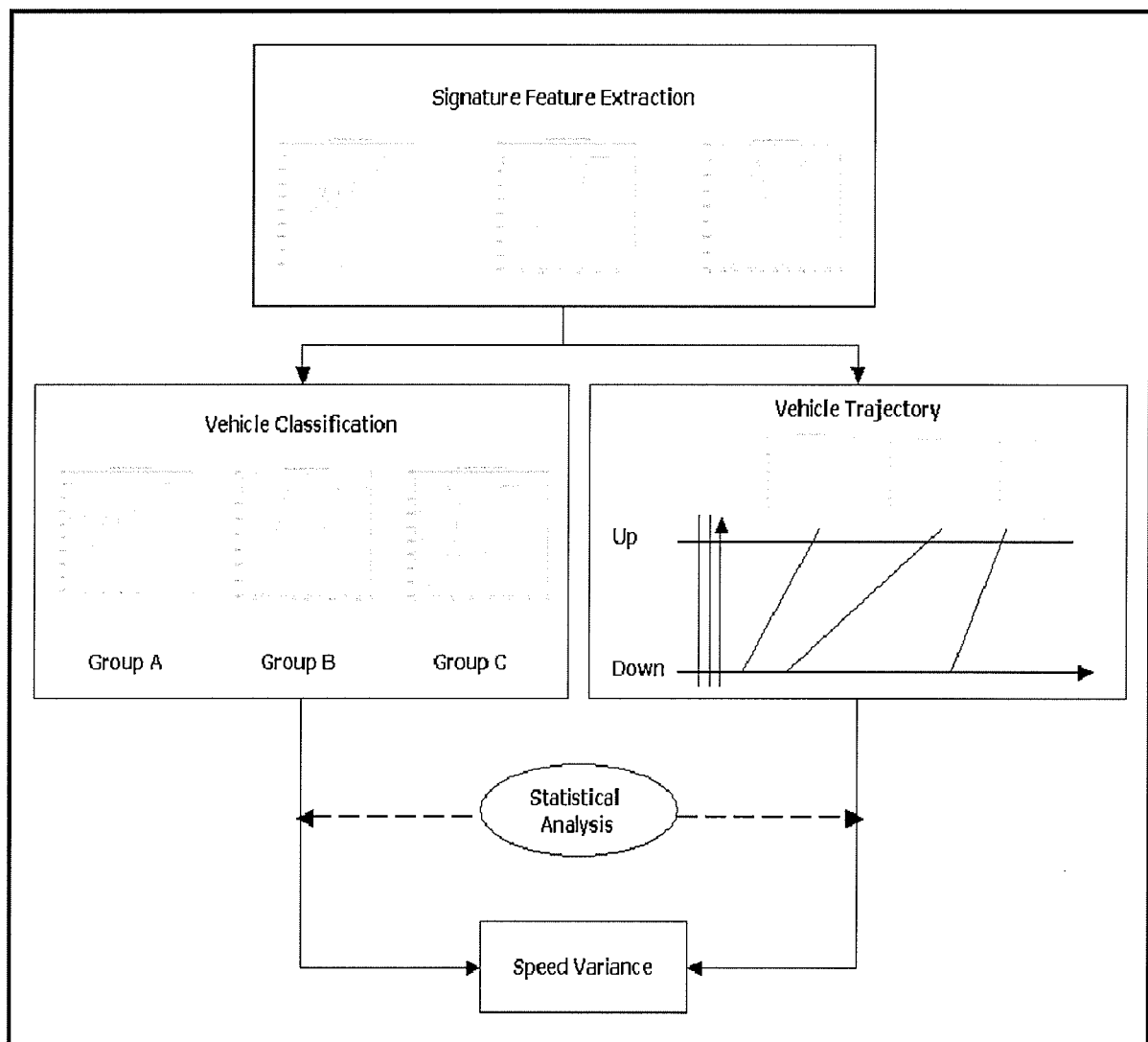


Figure 4. Overall Study Framework

Vehicle Classification

Vehicle classification is the process of the grouping vehicles based on their characteristics. As mentioned in earlier, vehicle signature is clearly the function of vehicle type and traffic conditions. Based on the extensive signature feature vector analysis, the heuristic method was implemented. Three vehicle features, electronic vehicle length, maximum magnitude, and degree of symmetry (DOS), were selected as algorithm inputs to yield nine vehicle groups. Detailed description on each vehicle group will be followed in the next section. Figure 5 illustrates proposed vehicle classification algorithm procedure.

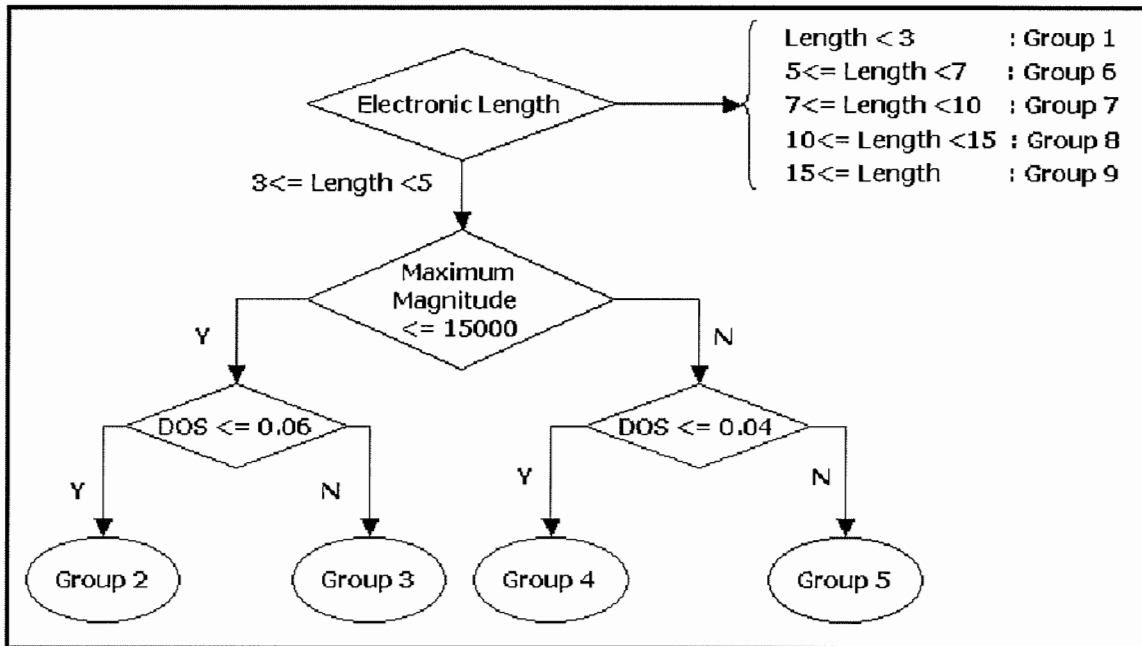


Figure 5. Vehicle Classification Flow Chart

Individual Vehicle Trajectory

As stated in previous section, each individual vehicle has its unique vehicle signature. Based on this uniqueness and traffic conditions, vehicles can be identified at different locations. This explains the core concept of individual vehicle trajectory acquisition and Figure 6 presents the overall procedure. Once, vehicles are traced useful and invaluable traffic information can be obtained and lane changing is one of those data. Details can be found from previous studies (17, 19, 21)

Hypothesis Test

Although the most ideal case is to trace all the individual vehicles, due to the various road traffic conditions, such as exactly same type vehicles passing detection station simultaneously, it was found out that 75-78% of vehicles are correctly identified (17). Therefore, a hypothesis test to decide to accept derived data as real world data should be performed. In this study the Kolmogorov-Smirnov (K-S) test was applied.

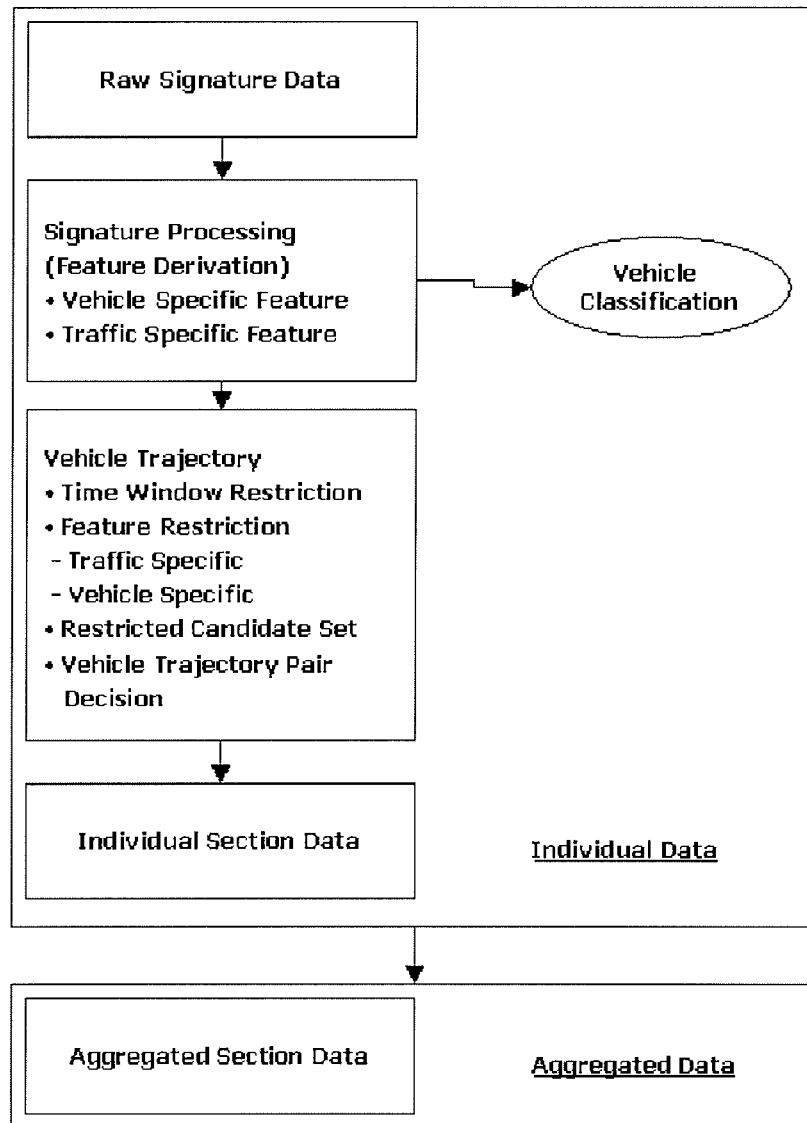


Figure 6. Vehicle Trajectory Derivation Procedure

Factor Analysis

The purpose of factor analysis is to describe the covariance relationships among many variables in terms of a few underlying, but unobservable, random quantities called factors. Its general objectives are data reduction and interpretation. Factor analysis is often used to study the correlations among large number of interrelated quantitative variables by grouping the variables into few factors. Therefore, after grouping, the variables within each factor are more highly correlated with variables in that factor than with variables in other factors. This will help to reduce the variables into small, but meaningful data structures. In most cases, factor analysis is more a

means to an end rather than an end in itself because it frequently serves as an intermediate step in much larger investigations, such as multivariate regression analysis in this study. Principal component analysis, which attempts to explain variance-covariance structure through a few linear combinations of the original variables, is applied as factor extraction method. Once the factors are obtained, factor rotation is followed to have a pattern where each variable loads highly on a single factor and has small-to-moderate loadings on the remaining factors. An analytical measure of simple structure known as the varimax method was used for the factor rotation. Final result will be applied as inputs for the statistical analysis model.

The main purpose of using factor analysis in this study is to choose one of the optimal input sets that would explain well the statistical model.

Statistical Model Building

Multivariate regression was used for the statistical model building. To meet the study objectives, statistical analysis and quantification of the relationship between speed variance and traffic variables, several models were examined by changing the input variables.

RESULT ANALYSIS

Study Site and Data Description

The Traffic Detector and Surveillance Sub-Testbed (TDS²), the study site of this paper, consists of two contiguous sites on the seven-lane I-405 freeway, south of Irvine. The section is about 0.7 mile long and is equipped with different traffic sensors in both upstream and downstream. The overall purpose of the TDS² is to provide a real-world laboratory for the development and evaluation of emerging traffic detection and surveillance technologies. As illustrated in Figure 7, double inductive loops are implemented for all lanes, and special cameras, that capture the horizontal images of each single vehicle passing over the detection zone, are installed on top of each lane. There are seven lanes in upstream, one that merges with the adjacent lane within the section. The left most lane is HOV lane. At downstream there are two HOV lanes, four mainstream lanes and one off-ramp lane. Figure 8 describes the lane configuration.

In this study two datasets were used. The first dataset was obtained from 15:00 to 15:30 PM on July 23rd, 2002. All the vehicles from 15:00 to 15:20 were manually identified at upstream and downstream stations. Hypothesis test for accepting the section derived data as real world data was based on this dataset because it has a true data distribution. The second dataset is from 7:20 to 7:40 AM on the same date that includes the morning peak and a wide range of speed variance. With the thirty - second aggregation interval, hundred points were generated for the proposed statistical analysis.

Section Variance KS Test

The result of KS test indicates that the derived section speed variance is the same distribution as true section speed variance. Therefore, the data from estimating individual vehicle trajectory can be applied to represent the real world phenomena.



Figure 7. Study Site Detector Deployment

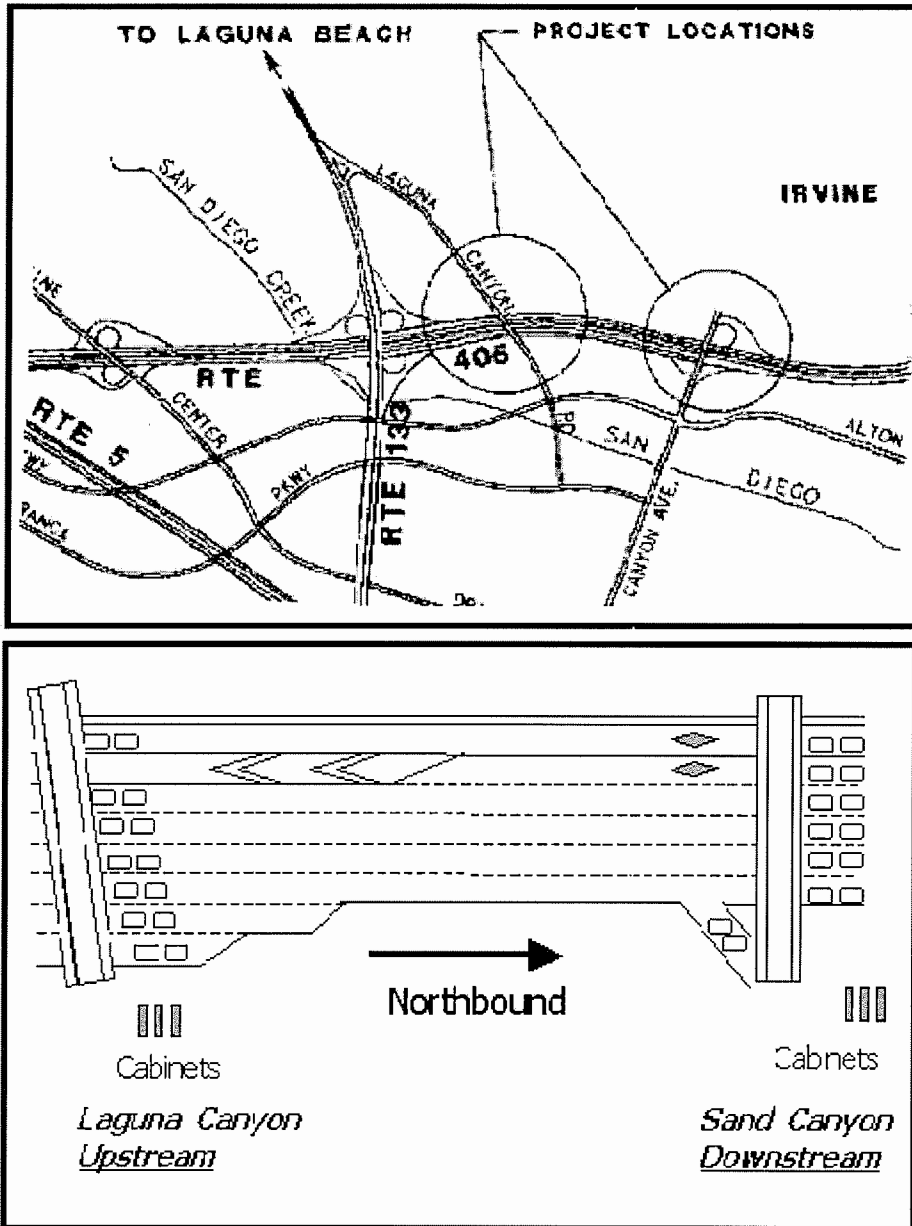


Figure 8. Study Site Lane Configuration

Vehicle Classification

Table 2 describes vehicle classification result. Vehicle types corresponding to each vehicle group are also presented.

For the group 1, 8, and 9, the classification rate was 100% because of their unique signatures. Group 2 shows the lowest correct classification rate and in most cases the corresponding vehicles were misclassified as either group 3 or group 4. In most cases for passenger car and minivan, the misclassification was found between these two groups rather than to other groups. For the group 7, one was categorized as group 6 because its length was just at the boarder of the threshold value. The overall performance was encouraging with 82 % correct classification rate

Table 2. Vehicle Classification Result

Group	Vehicle Type	Total Vehicle Number	Correct Classified Number	Correct Classification Rate
Group 1	Motorcycle	4	4	100
Group 2	SUV	474	327	68.99
Group 3	2 Axle 4 Tire Pickup, Van	392	337	85.97
Group 4	PC	1246	1023	82.10
Group 5	Minivan	124	105	84.68
Group 6	2 Axle 4 Tire	112	110	98.21
Group 7	2 Axle 6 Tire (7<= Length < 10)	37	36	97.3
Group 8	2 Axle 6 Tire (10<= Length < 15), Bus	43	43	100
Group 9	Big Trailer	54	54	100
		2486	2039	82.02

Statistical Analysis

Fraction of each vehicle class to total volume at each site, fraction of lane changing vehicles to total identified vehicle volume, upstream volume and downstream volume difference for each vehicle class within aggregation interval, and average section speed were chosen as possible input variables from aggregated individual vehicle trajectory data. Vehicle classes 1, 2, 3, 4, and 5 were grouped together as one single variable because no particular trend was found when examined the scatter plot with speed variance individually, but one trend was observed when aggregated value was investigated. Table 1 lists these variables in detail.

In this paper, two analysis approaches were introduced. The first approach examines the variance – covariance matrix of input variables using the factor analysis method. This will help to reduce the multiple variables into meaningful but fewer variables. Then those factor analysis outputs were applied as input variables of statistical analysis. The second approach is based on the assumption that vehicle class information and lane changing behavior will have high correlation with speed variance. Therefore the inputs were chosen from the various combinations of vehicle class and lane

changing data. In overall, these approaches share common statistical analysis method, multivariate regression model.

Table 3. Possible Input Variable Description

Category	Variable Name	Description
Vehicle Class	UC12345	(Volume of Vehicle Class A) / (Total Volume at Station)
	DC12345	
	UC6, DC6	
	UC7, DC7	
	UC8, DC8	
	UC9, DC9	
Volume Difference	C12345Diff	(Upstream Class A Volume) – (Downstream Class A Volume)
	C6Diff	
	C7Diff	
	C8Diff	
	C9Diff	
Point Volume	UpVol	Volume at each station
	DownVol	
Lane Changing	L0	(Volume of up and down lane difference “0” from Vehicle Trajectory Data) / (Total Vehicle Trajectory Volume at Downstream)
	L1	
	L2	
	L3	
	L4	

Factor Analysis

Above mentioned 22 variables were examined for the variance –covariance matrix. The main objective of factor analysis procedure is to derive variables that are least correlated for the input of multivariate regression model. This will help to obtain regression result without having the problem of multicollinearity. Therefore, this approach will also contribute to find one of the ideal combinations of input variables for statistical analysis model. Principal component analysis was applied for the factor extraction and Varimax method for the factor rotation. The eigenvalues according to the component number is plotted in Figure 9, the scree plot. According to the plot trend the optimal factor number is selected at the point where the eigenvalue drop becomes less steep. Figure 9 indicates the optimal factor number is 6. L0, L2, L4, UC7, DC8, and DC9 were the variables that are highly correlated with those factors and therefore will be used as one of the input sets for the multiple regression model.

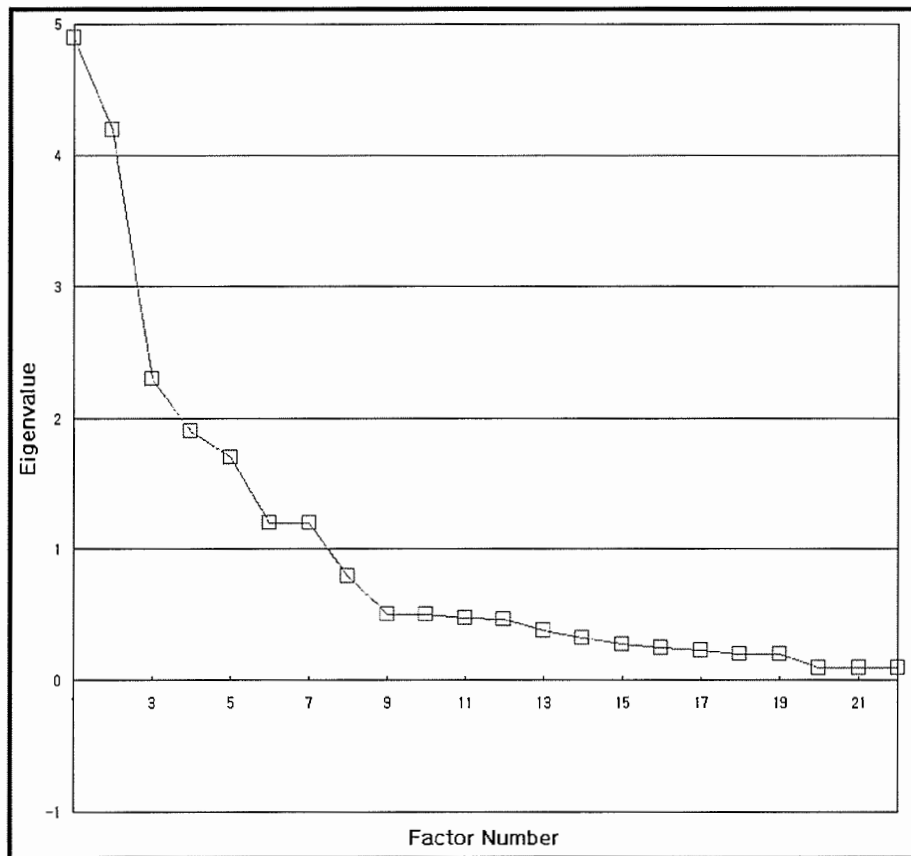


Figure 9. Scree Plot

Statistical Analysis Model (Model Development)

Based on the assumption that lane changing and vehicle class affect speed variance, the following models were constructed. Especially, to investigate long vehicles' impact on speed variance, the last four regression models are suggested. Table 4 summarizes proposed analysis models.

For most cases, the adjusted R^2 value was not as high as expected (above 0.7) but the value of each model suggests some correlation exists between speed variance and input variables. Especially, most of models' t statistics indicate the lane changing variables explain well the speed variability, particularly when the lane changing pattern is more than 4-lane difference. Statistical analysis results of models that include the variables associated with upstream and downstream volume difference showed that those variables, except for variables related to vehicle class8 and 9, are not significant enough to be considered. Therefore, in this paper, only the model that has volume difference for vehicle class8 and 9 is mentioned.

The assumption that long vehicle influence speed variance more directly is also confirmed from many models' results. However, the sign for the upstream long vehicle fraction (uc8) was not consistent through all the models involved. In case of downstream long vehicles, all analyses show negative relationship with the speed variance. This implies that vehicles that leave the section within the analysis interval, contribute to lessen the speed variance. Whereas in case of upstream,

the vehicle class 9, is always in positive sign correlation with the speed variance, meaning the entering vehicles tend to increase the speed variability.

Lane changing behavior is the one that shows definite clear pattern with the speed variance. Analysis shows that in case of L1, because the collinearity was so high with L0, in all models, one of these variables was excluded during the analysis process. It should be noted that the lane changing 4 always has a higher *t* statistic compared to other lane changing behavior in all models. This implies that the lane changing that is more than lane difference 4 is affecting speed variance in high degree.

Table 4. Model Summary

	Independent Variables	Adjusted R ²	F value	Comments
I	L0, L2, L4, UC7, DC8, DC9	0.485	8.645	Variables selected from factor analysis result
II	L0, L1, L2, L3, L4, UC12345, UC6, UC7, UC8, UC9 DC12345, DC6, DC7, DC8, DC9	0.613	6.467	L1, DC6, UC12345 variables excluded during the model development due to the collinearity
III	L0, L1, L2, L3, L4	0.416	10.025	L1 variable excluded For all the remaining variables, <i>t</i> statistics are significant
IV	UC12345, UC6, UC7, UC8, UC9 DC12345, DC6, DC7, DC8, DC9	0.386	4.162	Only four variables have significant <i>t</i> statistics
V	L0, L1, L2, L3, L4, UC12345, UC6, UC7, UC8, UC9	0.526	7.345	Lane changing related variables have significant <i>t</i> statistics
VI	L0, L1, L2, L3, L4, DC12345, DC6, DC7, DC8, DC9	0.530	7.456	Lane changing related variables have significant <i>t</i> statistics
VII	L0, L1, L2, L3, L4, UC8, UC9	0.453	7.589	All variables, except for UC8, have significant <i>t</i> statistics
VIII	L0, L1, L2, L3, L4, DC8, DC9	0.488	8.748	All variables, except for L3, have significant <i>t</i> statistics
IX	L0, L1, L2, L3, L4 UC8, UC9, DC8, DC9	0.564	8.562	All variables, except for L3, have significant <i>t</i> statistics
X	L0, L1, L2, L3, L4, C8Diff, C9Diff	0.494	8.937	All variables, except for L3, have significant <i>t</i> statistics

Model I was constructed based on the outputs from factor analysis. In most cases the *t* statistic was high enough to have a significant impact on speed variance except for UC6. Also, the collinearity problem was not found in this model.

In order to investigate driver's lane changing behavior impact, Model III was introduced. All variables related to lane changing were applied as inputs. During the model building procedure, L1 was eliminated due to the collinearity. Except for L0, the rest variables show positive sign relationship with speed variance, meaning that lane changing behavior tends to increase the speed variance.

Model VII, Model VIII, Model IX, and Model X are more dedicated for explaining lane changing and long heavy vehicles impact on speed variance.

Model VIII, IX and X were interesting in that most inputs, except for L3, have significant *t* statistics and high adjusted R² and *F* statistics at the same time.

In Table 5, detailed description on selected desirable models is presented.

Table 5. Selected Model Description

	Model (<i>t</i> statistics)	adjusted R ²	F Value
I	6.542 – 2.882L0 + 4.152L2 + 70.058L4 – 27.039DC8 – 10.781DC9 – 0.321UC6 (11.876) (-2.072) (2.457) (3.565) (-2.674) (-1.948) (-0.146)	0.485	8.645
III	6.169 – 4.410L0 + 5.154L2 + 11.090L3 + 44.150L4 (14.658) (-2.191) (3.025) (1.190) (2.228)	0.416	10.02 5
VIII	2.391 + 3.663L1 + 7.786L2 + 8.967L3 + 70.051L4 – 25.828DC8 – 10.337DC9 (1.744) (1.876) (2.818) (0.848) (3.496) (-2.521) (-1.859)	0.488	8.748
IX	6.352 – 2.895L0 + 3.418L2 + 3.679L3 + 60.740L4 – 30.636DC8 – 16.542DC9 + 11.115UC8 + 12.391UC9 (1.188) (2.713)	0.564	8.562
X	6 – 2.729L0 + 3.837L2 + 5.603L3 + 58.035L4 + 0.169C8Diff + 0.173C9Diff (14.884) (-1.373) (2.249) (0.618) (3.004) (1.197) (2.650)	0.494	8.937

CONCLUSION

The core contribution of this study is the statistical analysis between speed variance and driver's lane changing behavior - data which is not available from conventional traffic sensors. Results show that lane changing behavior within the section has significant impact on section speed variability, especially in case when the lane changing is more than four lanes. Investigation on vehicle heterogeneity also suggests that long vehicles have considerable influence on speed variance as well. Also, it should be noted that instead of point speed variance, the section speed variance, which demonstrates traffic changes more efficiently, is used. This study is more dedicated to present the correlation between speed variance and traffic factors rather than to build a

robust speed variance estimation method. Investigation and identification of factors influencing speed variance will help to establish countermeasures that will minimize speed variability, and thus improve traffic safety.

This study needs to be enhanced by using a dataset corresponding to longer period. Time series analysis can also contribute more to describe the speed variance relationship with the mentioned traffic variables. Also, finding other traffic variables and combining them with existing ones will help to improve the analysis.

Reference

1. Speed and Accidents : A Preliminary Report. Ministry of Transport and Communications, Ontario, Canada, 1974
2. Pisarski A. E., Deep-Six 55. Reason Foundation, Vol. 17, No. 6, 1986, pp. 32-35
3. Solomon, D., Accidents on Main rural Highways Related to Speed, Driver, and Vehicle. FHWA, U.S. Department of Transportation, 1964
4. Cirrillo, J. A., Interstate System Accident Research Study II, Public Roads, Vol.35, No.3, 1968, pp. 71-75
5. Munden, J. M., The Relation Between a Driver's Speed and His Accident Rate, Report LR 88. Road Research Laboratory, Crowthorne, England, 1967
6. Cerrelli, E. C., Safety Consequences of Raising the National Speed Limit from 55 mph to 60 mph. NHTSA, U.S. Department of Transportation, 1981
7. Garber, NJ; Gadiraju, R.. Factors Affecting Speed Variance and Its Influence on Accidents. Transportation Research Record 1213, 1989, pp. 64-71
8. Feng, C. Synthesis of studies on Speed and Safety. 80th Annual Meeting of the Transportation Research Board
9. Hughes, R., and Council, F., On Establishing the Relationships between Freeway Safety and Peak Period Operations : Performance Measurement and Methodological Considerations. 78th Annual Meeting of the Transportation Research Board
10. Corby, M. J., and Saccomanno, F. F., Analysis of Freeway Accident Detection. Transportation Research Record 1603, 1997, pp.80-89
11. Oh C., Oh J., Ritchie, S. G., and Chang, M. S., Real Time Estimation of Freeway Accident Likelihood. 80th Annual Meeting of the Transportation Research Board
12. Lee, C., Saccomanno, F., and Hellinga, B., Analysis of Crash Precursors on Instrumented Freeways. Transportation Research Record 1784 2002 pp 1-8
13. Elmberg, C. M., Effects of Speed Zoning in Urban Areas. M.S. thesis, Purdue University, May 1960
14. Garber, N. J., Gadiraju, R. , Impact of Differential Speed Limits on the Speed of Traffic and the Rate of Accidents, Transportation Research Record 1375,
15. Collins, J., Fitzpatrick, K., Bauer, K. M., and Harwood, D. W. Speed Variability on Rural Two-Lane Highways, Transportation Research Record 1658, ?, pp. 60-69
16. Fitzpatrick K., Carlson. P. , Brewer M., and Wooldridge M., Design Factors that Affect Driver Speed on Suburban Streets, Transportation Research Record 1751, 2001, pp. 18-25
17. Sun, C., Ritchie, S.G, Tsai, K., and Jayakrishnan, R., Use of Vehicle Signature Analysis and Lexicographic Optimization for Vehicle Reidentification on Freeways. Transportation Research Part C, Vol 7, No 4, 1999, pp. 167-185
18. Sun, C., and Ritchie, S. G., Individual Vehicle Speed Estimation Using Single Loop Inductive Waveforms. Journal of Transportation Engineering, Vol125, No6, 1999, pp.531-538
19. Ritchie, S. G., Sun, C., Oh, S., and Oh, C., Section Related Measures of Traffic Ssystem Performance : Prototype Field Implementation. California PATH Research Report, 2001, UCB-ITS-PRR-2001-32
20. Oh, S., Ritchie, S. G., and Oh, C. Real Time Traffic Measurement from Single Loop Inductive Signatures. Transportation Research Record 1804, 2002, pp. 98-106
21. Ritchie, S. G., Park, S., Oh, C.,and Sun, C., Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies – Phase I. California PATH Research Report, UCB-ITS-PRR-2002-15

22. Sun, C, Ritchie, S G. and Oh, S. , Inductive Classifying Artificial Network for Vehicle Type Categorization. *Computer-Aided Civil and Infrastructure Engineering*, Vol 18, No 3, 2003, pp. 161-172
23. SPSS Base 7.5 Applications Guide, SPSS INC, 1996
24. Johnson R.A., Wichern D. W., *Applied Multivariate Statistical Analysis*, Prentice Hall 3rd Edition, 1992